15.6 TIME-FREQUENCY BASED MACHINE CONDITION MONITORING AND FAULT DIAGNOSIS [0]

15.6.1 Machine Condition Monitoring and Fault Diagnosis

Machine condition monitoring is the process of checking a machine for abnormal symptoms. Fault diagnosis, on the other hand, means deciding the nature and the cause of the fault by examining the symptoms [1]. The article aims at providing a methodology for potential users interested in implementing techniques pertaining to the area of machine condition monitoring using time-frequency analysis (TFA). It also provides three examples and some relevant references. Although this article focuses on one-dimensional time-domain signals, its methodology can be extended to images and image sequences.

15.6.1.1 Machine Condition Monitoring

In modern manufacturing, the quest for automation and flexibility has resulted in machines performing extremely complex processes. The performance of such processes highly depends on the trouble-free operation of all the components. When a fault occurs, it is critical to detect it, isolate the causes, and take appropriate maintenance action at an early stage. This helps prevent faults from developing into an eventual major machine failure and interrupting the production cycle. Consequently a number of techniques have been developed which monitor certain parameters within the machinery allowing its condition to be determined. These monitoring techniques have become known as machine condition monitoring.

The predictive maintenance through condition monitoring and diagnosis can significantly improve product quality, improve worker safety, and reduce the costs of maintenance. This is achieved by (1) allowing the early detection of potentially catastrophic faults which could be expensive to repair, and (2) allowing the implementation of condition based maintenance rather than periodic or failure based maintenance. In these cases, significant savings can be made by delaying scheduled maintenance until it is more convenient or necessary.

An efficient condition monitoring technique is capable of providing warning and predicting the faults at early stages by obtaining information about the machine in the form of primary data. Through signal processing (SP), the critical information from these data is captured and correlated to the condition of the machine. Effectiveness depends on matching the SP algorithms to the characteristics of the monitored signals.

Two types of condition monitoring and diagnosis systems are widely used: off-line and on-line. In an off-line (periodic) monitoring system, the monitored signal is measured at pre-selected time intervals. This approach is routinely used for fault diagnosis and trend analysis. In an on-line (permanent) monitoring system the

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signal is continuously measured and compared with a reference level. This type of system is intended to protect machines and/or operators by providing a warning about a possible malfunction of the machine and/or an imminent shutdown to prevent catastrophic failure.

Traditionally, human operators, using a combination of sight and sound, have performed machine condition monitoring. Recently, automatic techniques have been proposed to replace human operators. Some of these techniques rely on direct measurements while the majority depend on indirect measurements. Direct methods use sensing techniques that directly measure the extent of the deterioration, such as tool wear, in a machine. Indirect methods may rely on sensing different machine parameters such as forces, acoustic emission, temperature, vibration, current, voltage, torque, strain, and images of the tools in question. In techniques based on indirect measurement, features indicative of condition are extracted from these monitored signals and correlated to give a measure of the extent, the nature, and the location of the fault [2].

15.6.1.2 The Four Stages of Condition Monitoring and Diagnosis

In general, machine condition monitoring, as a pattern recognition problem, consists of four stages: data acquisition, feature extraction, feature selection, and decision-making. Data are acquired using transducers and normally recorded in either analog or digital form on magnetic tape or computer disk. (In simple systems it may be possible to perform the analysis in real-time).

A critical step of condition monitoring and diagnosis is feature extraction. It is generally not practical to automatically determine the machine condition using the collected raw signals and therefore some transformation or processing is required. This transformation usually involves as a first step mapping the original data from time-domain to another domain, such as the frequency or time-frequency domains, where the differences between the normal and abnormal behaviors are much more apparent. In this new domain, features that best describe the characteristics of the process condition are extracted. Feature extraction techniques include statistical methods, power spectral methods, and time-frequency methods as detailed in Section 15.6.2. In some cases, where the dimension of the feature space (or the number of features) is high, the dimension can be further reduced by retaining only the most valuable features and eliminating those that give little or no additional information. This dimension reduction processes is called feature selection.

The decision-making or classifier stage can be viewed as a process that automatically correlates the feature set, obtained from the previous stage, to the machine conditions [3]. It is usually done through supervised learning, where the operator instructs the computer of the possible patterns in the feature sets and relates them to the machine conditions. Sometimes it is difficult to generate data that reflects all uncertainties and differences within one class or group of faults in an experiment setting. In this case, an unsupervised learning strategy is used. Unsupervised learning is a task in which the number of classes is not known before classification and there

are no labeled training features available. The classifier itself should be capable of exploring the extracted features and deciding about the number of classes. Typical automatic or computer decision-making methods include pattern recognition, fuzzy logic, decision trees, and artificial neural networks. Ideally, there exists a one-to-one correlation between feature sets and machine conditions.

An alternative approach is to monitor the features and spot trends in them and thus predict failure. The decision to replace the faulty part is often taken when the feature crosses a given threshold [1].

15.6.1.3 Classical Signal Analysis Methods for Feature Extraction

Classical methods used for feature extraction can be classified into time domain and frequency domain.

Time Domain Methods: Probably the simplest approach proposed for fault detection in the time domain is through the measurement of the energy (mean square value) of the monitored signal. The method relies on the fact that as the machine's condition deteriorates, the vibration energy is expected to increase. Another approach is to use statistical parameters for fault detection. By treating the monitored signal as random variable, higher-order statistical moments, cumulants, and measures such as crest factor can also be used as features. Nonlinear signal based techniques have also been used for condition monitoring and fault diagnosis. In [4], for example, the correlation dimension was extracted from raw time-series acceleration data (collected from a rolling-element bearing) and used as a feature for detecting faults. Other methods such as level crossing, bandpass filtering, shock pulse, and autoregressive modeling are used (see for example [5]).

Frequency Domain Methods: The basic principle of spectral analysis is based on the fact that the spectrum of the monitored signal changes when faults occur. The nature and extent of the change depends of the nature of the fault and the machine being monitored. The condition of the machine is estimated through monitoring the change in the spectrum or a number of discriminating features extracted from the spectrum of the measured signal. These features are usually chosen as some specific frequency components that depend on the type of machine and the nature of the fault. They are compared to references established when the machine was known to work properly under similar conditions, and an appropriate decision is taken when the feature vector deviates from the reference by more than a predetermined threshold. In [6], the different changes in the vibration spectrum of rotating machines are surveyed and linked to different types of faults. Also, in [7, ch. 11] the most frequent failure modes are identified for the different machine-train components such as drives, steam turbines, gearboxes, and generators. For each component, a number of specific vibration frequencies are monitored for the diagnosis of incipient problems. These frequency-domain features, depending on the component and the nature of the failure, may include defect frequencies, the fundamental and harmonics of the rotational speed, the line frequency, the slip frequency, and

the tooth-mesh frequencies and the sidebands that surround them. Higher-order spectra such as the bispectrum and trispectrum are also used as a basis for condition monitoring. In [8], the bispectrum is used to analyze the acceleration signal obtained from a stamping process and to extract features related to defective parts.

15.6.1.4 Nonstationary Signals in Machines

Limitations of Classical Methods: Traditional time-domain and spectral analysis techniques have several shortcomings. For example, the Fourier transform is unable to accurately analyze and represent a signal that has non-periodic components such as a transient signal, as it is based on the assumption that the signal to be transformed is periodic. Another deficiency of the traditional spectral analysis is its inability to provide any information about the time dependency of the frequency content of non-stationary signals (see Article 1.1 for more details).

Motor current, for example, is well known to be a nonstationary signal whose properties vary with respect to the time-varying normal operating conditions of the motor, particularly with load. Also, for the case of rotating machines, the presence of certain frequency components within the spectrum has been shown to be an indication of a fault condition. However, since some of these frequencies depend on the rotational speed, it is not possible using spectral analysis to determine these frequencies when the bearing runs at variable rotational speed. Recent works have stressed the importance of machine monitoring during the transient states—such as start-up, shutdown, and acceleration periods—because some machine failures happen during these types of transition periods. Transient signals can be a good source of information about machine condition that is not available during steady states. Fourier transform based methods are known to be inadequate in representing this type of signals since the transient event can hardly be approximated by sines and cosines. For these reasons, Fourier transform based methods are unsuitable for machine monitoring in the above-mentioned circumstances [9].

The Need for Time-Frequency Methods: To overcome the shortcomings of the traditional spectral analysis techniques, nonstationary signal analysis approaches have been introduced. The most frequently used methods in the area of machine condition monitoring and diagnosis are quadratic time-frequency distributions (TFDs) and time-scale analysis (mainly the wavelet transforms (WT)). These methods represent the signals in a wider time-frequency space that allows easier and more precise discrimination between fault and normal machine conditions. Using time-frequency techniques, such as the Wigner-Ville distribution (WVD), a framework was developed that provided robust detection and classification schemes for helicopter gearbox faults [10]. This was achieved by showing that different faults produced different patterns in the time-frequency plane. The WVD-based patterns of vibration and acoustic signals were also used to detect faults in a number of machines and machine components such as engines [11] and gearboxes [12]. Other time-frequency distributions such as higher-order Wigner-Ville moment distributions [13] and reduced-interference time-frequency distributions (RIDs) [14] are used

for machine monitoring and diagnosis. Most of these methods, however, are visual-based detection/classification techniques which are meant to show the effectiveness of the respective TFDs for early detection of faults. The other methods are used as automatic feature extractors in an overall classification process. Some of the features extracted are amplitude values of the contour plots [12] and singular values of the TFD [14].

Due to their ability to represent nonstationary signals in general, and to detect and localize transient events in particular, wavelet transforms (both continuous and discrete) have been readily adopted in machine condition monitoring and diagnosis. They were used in detecting a large number of faults in different machines or machine components such as turning and drilling machines [1], gears or gear trains [15], and bearings [16]. As in the case of the TFDs, some of the proposed methods are used as feature extractors whose output is fed to a detector/classifier [1].

15.6.2 Time-Frequency Analysis Methods

Articles in Chapters 1 to 5 present detailed background on different time-frequency methods. The two most widely used time-frequency methodologies are the quadratic time-frequency distributions and the wavelet transforms. These two classes of representations are related through the STFT and the Gabor transform (see Articles 2.3 and 2.7). TFDs are suitable for large BT signals (see Chapter 1) while WTs give best results when used with low BT and transient signals.

15.6.2.1 Quadratic Time-Frequency Distributions

For nonstationary signals, the Wiener-Khintchine theorem indicates that the time-varying power spectral density, $S_x(t,f)$, of a real random signal $x(t)$ is related to the time-varying autocorrelation function, $R_x(t,\tau)$, by a Fourier transform relation; that is

$$S_x(t,f) = E\left\{W_x(t,f)\right\} = \int_{-\infty}^{\infty} R_x(t,\tau)\, e^{-j2\pi f\tau}\, d\tau. \tag{15.6.1}$$

The expression $S_x(t,f)$ given by Eq. (15.6.1) is the Wigner-Ville spectrum (WVS), which is the expectation value of the Wigner distribution (WD) $W_x(t,f)$. For practical reasons, $x(t)$ is replaced by its analytic associate $z(t)$ (see Sections 1.2.2, 1.2.3 and 2.1.4). It was shown that an estimate of $S_z(t,f)$ can be obtained from the quadratic class of TFDs [17], which was expressed in Section 3.2.2 as

$$\rho_z(t,f) = W_z(t,f) \underset{t\ f}{*\,*} \gamma(t,f) \tag{15.6.2}$$

where $\gamma(t,f)$ is a two-dimensional kernel window which is application dependent, $W_z(t,f)$ is the WVD, and $\underset{t\,f}{**}$ indicates a double convolution. The example in Section 15.6.3.1 illustrates an application of the WVD to machine condition monitoring.

The kernel window, $\gamma(t,f)$, characterizes a particular time-frequency distribution and is generally chosen so as to obtain the best possible time-frequency resolution [14] (see Article 3.3 for more details).

15.6.2.2 Wavelet Transforms

Wavelet transforms are the localized equivalent of the Fourier transform. They provide a powerful tool for representing local features of a signal.

A finite-energy signal $x(t)$ can be represented by its Fourier transform $X(f)$:

$$x(t) = \int_{-\infty}^{\infty} X(f)\, e^{j2\pi f t}\, df \quad \text{where} \quad X(f) = \int_{-\infty}^{\infty} x(t)\, e^{-j2\pi f t}\, dt. \tag{15.6.3}$$

Thus, the FT decomposes the time-domain signal into linear combinations of harmonics $e^{j2\pi f t}$. The wavelet transform (WT) is defined in the similar manner except that the harmonics are replaced by a series of wavelet basis functions given by [18]

$$\psi_{\tau s}(t) = \frac{1}{\sqrt{s}}\, \psi\left(\frac{t-\tau}{s}\right) \tag{15.6.4}$$

where τ and s are the translation and dilation (scale) parameters respectively. The function $\psi(...)$ is the transformation function called the mother wavelet. Using wavelet bases, the time-domain signal can be represented as

$$x(t) = \frac{1}{c_\psi} \int_{-\infty}^{\infty} \int_{0}^{\infty} \Psi_x^\psi(\tau, s)\, \frac{1}{\sqrt{s}}\, \psi\left(\frac{t-\tau}{s}\right) \frac{ds}{s^2}\, d\tau \tag{15.6.5}$$

where

$$\Psi_x^\psi(\tau, s) = \int_{-\infty}^{\infty} x(t)\, \frac{1}{\sqrt{s}}\, \psi^*\left(\frac{t-\tau}{s}\right) dt \tag{15.6.6}$$

c_ψ is a constant that depends on the wavelet used and $\Psi_x^\psi(\tau, s)$ is the continuous wavelet transform of the signal $x(t)$. A number of mother wavelets have been proposed, such as the Mexican hat wavelet and the Morlet wavelet [18].

The discrete version of the WT is called discrete wavelet transform (DWT). It is realized by first discretizing the parameter scale s on a logarithmic grade. The time parameter is then discretized with respect to the scale parameter; that is a different sampling rate is used for every scale. In other words, the sampling is done on a dyadic sampling grid. With this sampling, a signal $x(t)$ can be decomposed into orthogonal basis functions (scaled and shifted versions of the mother wavelet ψ); that is [18]

$$x(t) = c_\psi \sum_{l} \sum_{k} a_{lk}\, s_0^{-l/2} \psi(s_0^{-l/2} t - k\tau_0) \tag{15.6.7}$$

where

$$a_{lk} = \int_{-\infty}^{\infty} x(t)\, s_0^{-l/2} \psi(s_0^{-l/2} t - k\tau_0)\, dt \tag{15.6.8}$$

with τ_0 and s_0 being positive constants usually taken as 1 and 2 respectively. The integer l describes the different levels of wavelets, and k covers the number of wavelets in each level.

The wavelet transform allows localization in both the time domain via translations of the mother wavelet, and in the scale (frequency) domain via dilations. The wavelet is irregular in shape and compactly supported, thus making it an ideal tool for analyzing signals of a transient nature. Irregularity of the wavelet basis lends it to analysis of signals with discontinuities or sharp changes, while the compactly supported nature of wavelets enables temporal localization of a signal's features.

The dilation function of the discrete wavelet transform can be represented as a tree of low- and high-pass filters, with each step transforming the low-pass filter. The original signal is successively decomposed into components of lower resolution, while the high-frequency components are not analyzed any further.

In contrast with the regular DWT, discrete wavelet packet analysis (DWPA) can significantly increase the versatility and power of the DWT. Unlike the DWT, DWPA utilizes both the low frequency components (approximations), and the high-frequency components (details). From this family of bases, a method for choosing the optimum scheme for a particular signal can be developed [18]. The two examples in Sections 15.6.3.2 and 15.6.3.3 illustrate the applications of DWT and DWPA to machine condition monitoring.

15.6.3 Examples of Condition Monitoring Using TFA

To illustrate how both time-frequency distributions and wavelet transforms are used in condition monitoring and diagnosis, we summarize three methods selected from the literature. These examples illustrate the time-frequency methodology adopted in this increasingly important area of engineering.

15.6.3.1 Gearbox Fault Detection Using Wigner-Ville Distribution

We consider the detection of a broken tooth in a spur gear using the WVD as the basis for feature extraction and pattern recognition techniques for classification [12].

Data Acquisition: The system considered is composed of a 24-tooth input gear driven by an electric motor and meshing with 16 teeth of a pinion whose rotational frequency is 37.5 Hz. The applied load was 70% of the maximum load. The study simulated five fault types, each involving the partial or total removal of one or more teeth. In particular, the faults were the removal of 25, 50, 75, and 100 percent of the face-width at a given radius, plus the same defect with 100% advancement on two pinion teeth. The acceleration vibration signal obtained from the above-mentioned system was low-pass filtered and sampled at a rate of 6.4 kHz.

Feature Extraction: The vibration signal is synchronously averaged in order to remove any periodic events not exactly synchronous with the gear of interest and to reduce the effects of noise and vibration sources other than that of the gear. In an industrial environment, where the problem of noise may become critical, efficient time-frequency based signal-cleansing techniques such as time-frequency peak filtering [19] (see also Article 11.4) may be required. The averaged signal is then transformed to the time-frequency domain using the pseudo-WVD (discrete

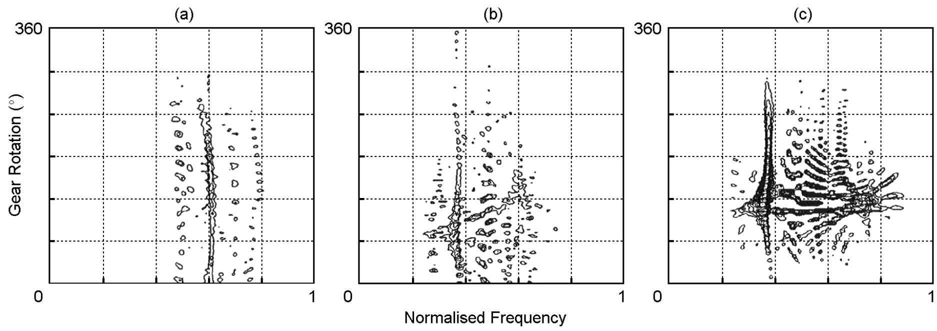


Fig. 15.6.1: Weighted WVD of the residual signal: (a) normal condition of the spur gear; (b) one broken tooth with 50% fault advancement; (c) one broken tooth with 100% fault advancement.

WVD) with a Hamming window. The negative values of the WVD are set to zero and the resulting distribution is normalized. The results are displayed in the form of contour plots. To enhance the sidebands around the meshing frequencies, the residual signal is obtained by removing the meshing harmonics using a band-stop filter. The extracted features are the amplitude values of the contour plots (see Fig. 15.6.1).

Feature Selection: To reduce the dimension of the feature vector, a selected number of WVD cross-sections at and around a chosen meshing frequency are selected.

Decision Making: Two classification approaches are considered: statistical and neural pattern recognition. In the first approach, to assign the feature vector from the last stage to one of the K classes considered, the Mahalanobis distance was chosen as the similarity measure. This measure is given by

$$d = \left[\sum_{k=1}^{K} (\vec{y} - \vec{\mu_k})^T \, \Sigma_k^{-1} (\vec{y} - \vec{\mu_k}) \right]^{1/2} \tag{15.6.9}$$

where $\vec{y}$ is the feature vector and $\vec{\mu_k}$ and Σ_k are the mean vector and covariance matrix representing the k^{th} class. The study considered only two classes; namely normal (no fault) and abnormal (fault) and used only one template representing the normal condition. In the second classification approach a neural network was trained in a supervised mode using the back-propagation algorithm [12].

15.6.3.2 Fault Diagnosis of Rotating Machinery Using Wavelet Transforms

In this example, the problem is to detect faults in a model drive-line consisting of various interconnected rotating parts that include a vehicle gearbox, two bearing housings, and an electric motor. All these parts are connected by flexible couplings and loaded by a disk brake as seen in Fig. 15.6.2 [20].

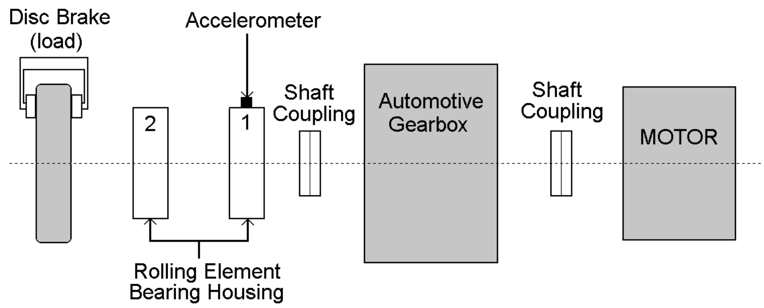
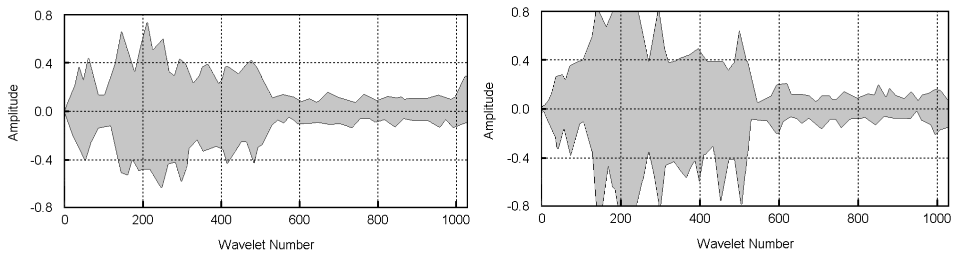


Fig. 15.6.2: Schematic presentation of the model drive-line.



(a) Envelope of the WT of a vibration signal representing a normal condition.

(b) Envelope of the WT of a vibration signal representing a faulty gear.

Fig. 15.6.3: WT of normal and faulty condition of the vibration signal.

Data Acquisition: Of the five gears (four forward and one reverse) only the reverse gear pinion is used in the experiment. On the gear pinion, two types of localized faults were simulated: a small "blip" of 2mm diameter on one tooth, and a triangular fracture on the face of one tooth. On the bearing housing, one fault was simulated by introducing a 1mm fracture across the inner race (Fig. 15.6.2). This gave six combinations of conditions for the pinion and housing, five of which represented fault conditions. An accelerometer was used to obtain the vibration signal from the bearing housing.

Feature Extraction: The vibration signals were transformed to the time-scale domain using the Daubechies 4th-order wavelet (D4) (see Fig. 15.6.3). After the transformation of the whole signal into the wavelet domain, a threshold value was chosen. This value was selected to be above the dominant component of the reference (normal) signal. The 10 most dominant amplitudes of the signals above the threshold value were selected to represent half of the feature vector. The other half consists of the 10 corresponding wavelet numbers (indicating both time and scale). As the number of features (20) is not large, no feature selection was needed.

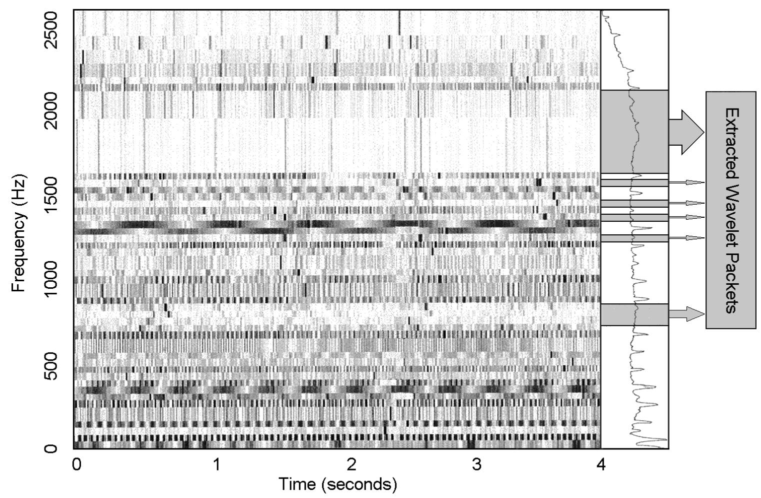


Fig. 15.6.4: DWPA representation of the vibration signal showing wavelet packets selected by ANFIS.

Decision Making: The classification was achieved using a two-layer neural network with sigmoid nodal function trained in a supervised mode using the back-propagation algorithm [20].

15.6.3.3 Extraction of Bearing Fault Transients Using DWPA

This example exploits the multiple band-pass filtering capability of the DWPA for the extraction of rolling-element bearing fault-related components. An algorithm is trained to recognize three types of localized faults; namely inner race, rolling element, and outer race faults [21].

Data Acquisition: The vibration signals are obtained from a rolling-element bearing test rig with a rolling-element fault and an operating speed of 60 rpm.

Feature Extraction: The extraction of high-frequency transients due to bearing impact resonance is achieved via best-basis DWPA representation using the Daubechies wavelet of order 20 and an adaptive network-based fuzzy inference system (ANFIS). ANFIS is a transformational model of integration where the final fuzzy inference system is optimized via artificial neural network training. Before the neuro-fuzzy network is trained (using wavelet packets extracted from vibration signals), suitable input parameters to train the network are selected. These parameters are kurtosis (a measure of spikiness) and the spectrum peak ratio (an indication of the presence of localized defects). The network is then trained using wavelet packets characterizing the above-mentioned types of faults. Fig. 15.6.4 illustrates how this method facilitates the extraction of bearing-fault-related components from a signal while rejecting the unwanted harmonics. The wavelet packets identified by ANFIS as containing bearing fault-related features are indicated on the figure [21].

15.6.4 Summary and Conclusions

Time-frequency analysis methods are applicable to the area of machine condition monitoring and diagnosis. They are capable of efficiently and unambiguously characterizing a large number of faults. TFA methods are used for detection, classification, and monitoring the progression of the faults and wear with time. This enables prediction and prevention of catastrophic failures. Time-frequency analysis techniques, in the form of either TFD or WT, are used as both visual indicators of the presence of faults and as a feature extractor in a fully automated pattern recognition process.

Articles 11.2 and 15.2 of this book describe two other time-frequency approaches to machine condition monitoring.

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